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Neutrosophic Fuzzy Hierarchical Clustering for Dengue Analysis in Sri Lanka

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Abstract: In the structure of nature, we believe that there is an underlying knowledge in all the phenomena we wish to understand. Mainly in the area of epidemiology we often tend to seek the structure of the data obtained, pattern of the disease, nature or cause of its emergence among living organisms. Sometimes, we could see the outbreak of disease is ambiguous and the exact cause of the disease is unknown. A significant number of algorithms and methods are available for clustering disease data. We could see that literature has no traces of including indeterminacy or vagueness in data which has to be much concentrated in epidemiological field. This study analyzes the attack of dengue in 26 districts of Sri Lanka for the period of seven years from 2012 to 2018. Clusters with low risk, medium risk and high risk areas affected by dengue are identified. In this paper, we propose a new algorithm called Neutrosophic-Fuzzy Hierarchical Clustering algorithm (NFHC) that includes indeterminacy. Proposed algorithm is compared with fuzzy hierarchical clustering algorithm and hierarchical clustering algorithm. Finally the results are evaluated with the benchmarking indexes and the performance of the clustering algorithm is studied. NFHC has performed a way better than the other two algorithms.

Keywords: Dengue; Hierarchical clustering; Fuzzy hierarchical clustering; Neutrosophic Logic

1. Introduction

Emerging and re-emerging infectious diseases which are transmitted to the environment is a great threat to human living. The infections can take many forms and it can seriously affect human health. Dengue is one among the disease which causes severe outbreaks in many regions of the world. Its prevalence, incidence and geographic distribution are demanding a divisive applicable plan for control measures against dengue fever. In this case the complete structure of data and regions affected by dengue has to be known. Many situations exist that the ambiguity arises in finding a solution to the problem. Clustering and Classification are the most commonly encountered knowledge-discovery technique. Clustering is used in numerous applications such as disease detection, market analysis, medical diagnosis etc. The study concentrates on Sri Lankan dengue data analysis. Dengue fever occurs in the background of heavy rain and flooding and has affected almost26 districts in Sri Lanka. The country has reported 51659 cases in the year 2018 and approximately 41.2 % cases identified in western province alone[1]. In Pakistan, dengue has progressed towards becoming a risk for general wellbeing because of inaccessibility of vaccination, unclean water, highly populated territories and low quality of sanitation and sewage [2]. There have been a number of researches done on dengue fever diagnosis and numerous methods have been proposed using classification and clustering techniques for dengue analysis. G.P.Silveria proposed evolution technique of dengue risk analysis or prediction using the model Takagi-Sugeno. Takagi-Sugeno model included parameters such as human population density, density of potential mosquito breeding and rainfall. The fuzzy rules were developed using partial differential equations for Low, Medium and High dengue affected areas. The uncertainty factor considered in this study is the breeding period and the maturation of mosquito eggs and Silveria considered rainfall as a factor for the increase or decrease in the population of mosquitoes [3]. The selection of Neutrosophic approach has increased in group decision making in vague decision environment. Neutrosophic approach with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)[4] is considered for decision making process to deal with the vagueness and uncertainty by considering the data for the decision criteria. Neutrosophic environment provides a new technique in Multi Criteria Decision Making problem. Author Abdel-Basset M [5], has developed and integrated Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) into Decision-Making Trial and Evaluation Laboratory (DEMATEL) on a neutrosophic set that handles to overcome the ambiguity or the lack of information. He has applied on project selection criteria where the best alternatives are provided by the neutrosophic approach.

This paper mainly focuses on the finding of Dengue affected areas using the clustering technique found. The clusters are formed as low risk, medium risk and high risk areas. It helps the public sectors to concentrate particularly on that area for the remedial measures that are to be considering for the wellbeing of the society. Based on the neutrosophic approach, the clustering for the low risk, medium risk and high risk areas are identified and clustered.

2. Related Work

The ambiguity or uncertainty representation or handling of incomplete knowledge becomes a vital problem in the field of computer science. Researchers from various fields have dealt with vague, indeterminate, imprecise and sometimes insufficient information of uncertain data. The concept of uncertainty is usually handled by probabilistic approach. Soft computing techniques also deals with these problems such as called fuzzy sets [6] and intuitionistic fuzzy sets [7] and rough sets. Fuzzy logic is a collection of mathematical values for representing and understanding is based on membership degrees rather than the crisp membership of traditional binary logic. It leads to more human intelligent machines as fuzzy logic tries to model the human feeling of words, decision-making and common sense[8].

Unlike Boolean's two-valued logic, Fuzzy logic is multi-valued logic. Matrices play an important role in representation of the real world problems of science and engineering. Therefore, a few authors have proposed a matrix representation of fuzzy sets and intuitionistic fuzzy sets [9,10,11,12,13,14,15,16,17]. Fuzzy set and Intuitionistic Fuzzy Set deals with the membership and non-membership values. Membership value shows the truthiness of the algorithm which is classified or clustered. Non-membership values show the falsity of the data that it doesn't belong to that class.

For some reasons, the calculation of non-membership value is not always possible as in the case of membership values. So, there exists some indeterministic that part depicts the ambiguity in fuzzy logic. Subsequently, Smarandache [18, 19] introduced the term Neutrosophic Set (NS), which is formed as a generalization of classical set, fuzzy set, intuitionistic fuzzy set. The literature [20-24] shows the growth of decision-making algorithms over neutrosophical set theory.

Neutrosophic logic that shows the clear separation between the" relative truth" and" absolute truth" while the fuzzy logic does not show any separation. Smarandache Florentine proposed the concept of neutrosophic logic based on nonstandard analysis by Abraham Robinson in 1960s. Generally, we can say that the available disease information in inherently unclear and unpredictable. In real life issues, an element of indeterminacy exists and in this respect, neutrosophic logic can be used. Neutrosophic logic generalizes fuzzy, intuitive, boolean, para-consistent logic etc.

In many medical diagnosis and study of diseases, the indeterminacy or falsity in the input is not captured so far. It is seen from the literature that the concept of neutrosophic logic is not applied much on medical diagnosis. Neutrosophic clustering technique is neither employed nor applied to any medical applications. Some of the applications of neutrosophic logic are Social Network Analysis, Financial Market Information, Neutrosophic Security, Neutrosophic cognitive maps, Application to Robotics etc.

2.1 Machine Learning on Dengue

Many authors have concentrated on Machine Learning algorithms for classification and prediction of various diseases. In over 100 nations, dengue is endemic and causes an estimated 50 million infections per year. Nearly 3.97 billion individuals are at danger of infection from 128 nations [25]. Machine Learning algorithms such as Regression Models, Decision Tree, Artificial Neural Network, Rough Set Theory, Support Vector Machine etc. are successfully applied [26]. Daranee Thitiprayoonwongse et al proposed a hybrid technique combining a decision-making tree with a fuzzy logic approach to constructing a model for dengue infection. Author obtained a set of rules from decision tree and transformed to fuzzy rules. The results were better by combining fuzzy and decision tree approaches [27]. Torra [28], has proposed a fuzzy hierarchical clustering for representing the documents. Fuzzy hierarchical clusters are used in order to assure that the clusters are small enough by giving low information loss.

This research mainly focuses on clustering of Dengue disease in various parts of Sri Lanka. Increased risk to infectious diseases was recognized as one of five main emerging threats to public health resulting from the changes in the natural environment [29]. Diseases caused by mosquitoes are a specific danger to humans. The danger of transmission relies on climate variables that regulate mosquito habitat development [30-32]. This paper discusses the possibilities to exploit neutrosophic logic in epidemiology domain. In many cases, the representational parameters which include temperature and humidity as mentioned by [30-32] the climatic variables could also be a part in spread of disease. Most of the cases are rare that all the external parameters are considered, which leads to a chaos about conclusion to be drawn.

So the developed system should adapt to the conditions that are uncontrollable or unanticipated. In this case indeterminacy plays an important role. The concept of indeterminacy is handled or explained in a improvised way by neutrosophic logic. A better approach for all the above is Neutrosophic logic.

3. Proposed Work

Clustering can be seen as an practical problem in pattern recognition in unsupervised learning. Problems can be size of dataset, number of clusters to be formed, there is no ground truth solution unlike classification problems. The goal is to partition the data set into a certain number of natural and homogeneous sets where each set’s elements is as similar as possible and different from the other sets. In real world applications, cluster separation is a fuzzy concept and therefore the idea of fuzzy subsets provides particular benefits over standard clustering [33]. This research proposes a hybridized technique for hierarchical clustering by amalgamation of fuzzy and neutrosophic approach. There by, the proposed algorithm gains the benefits of addressing imprecise, indeterministic, vague and uncertain data.

3.1. Hierarchical Clustering (HC)

In the process of hierarchical clustering, a distance matrix (D) is constructed where; d_{ij} is the distance between the cities. During clustering, i^{th} and j^{th} locations are merged into a cluster and distance matrix is updated. Eventually, the cities are merged based on the similarity measure and the dimension of D gets reduced on every step of merging. Hierarchical clustering is categorized based on the method of merging. It includes Single, Complete, Average, Centroid, Median and Ward. Merging clusters based on minimum distance between each element is called single linkage clustering. Clustering based on maximum distance between each element is complete linkage clustering, clustering the mean distance between each element is average linkage clustering, clustering is done by mean values of one group with the mean values on other group elements is centroid clustering. To overcome the disadvantage of centroid method the median of two groups are clustered is called median linkage clustering. Median linkage clustering is suitable for both similarity and distance measures. Wards method calculates the sum of the squares of the distance between the elements P_i and P_j, where P_i and P_j are the location of the elements in i^{th} and j^{th} positions.

The distance matrix is formed by using the Euclidean equation. Single, complete and average link are defined by the way of merging the cities based on nearest, farthest and average distance respectively.

$$d_{ij} = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \tag{3.1}$$

Where *i,j* are the location of cities and *n, k* are the number of cities.

Distance matrix here with dimension of 26×26 is formed. It is constructed on the basis of equation 3.1.Once the distance matrix is formed and based upon the method of hierarchical clustering, clusters are generated.

3.2. Fuzzy Hierarchical Clustering(FHC)

Given a set of objects, a fuzzy hierarchical framework has been implemented to construct clusters. The methodbegins to establish a fuzzy partition that uses the membership formula[34]. The membership matrix is calculatedusing the equation 3.2 which gives distance between each of the object, here it represents the cities.

$$\mu_{ik} = \left[\sum_{j=1}^{n} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/m^{`}-1} \right]^{-1} \tag{3.2}$$

where n is the number of locations, m is the weighting parameter or fuzzifier, r is the number of iterations used for convergence. There is no theoretical optimumchoice of m in literature. The range is usually between 1.25 - 2 [35] and here we have choosen value 2. Theinitial membership matrix(μ) is formed using equation (3.2). We have formed a fuzzy measure for objects.Here one object can belong to various clusters with the varying membership values ranging from 0 to 1. Valuesfalling between these endpoints (from low toextremely favorable clustering) were mapped as membershipdegrees. The non-membership value also called as falsity value, represented as $\vee$ [36]. It is calculated using thefollowing equation,

$$\vee_i = \frac{1-\mu_i}{1+\lambda\mu_i} \tag{3.3}$$

where, λ is the weighted parameter value ranging from 0 to 1. Here the value of λ is taken as 0.8.

3.3. Neutrosophic Fuzzy Hierarchical Clustering(NFHC)

The notion of a neutrosophical set was initially proposed by Smarandache [37]. A neutrosophical set A isdefined by a universal set X with truth-membership function T_A, a falsity-membership function F_A and anindeterminacy-membership function I_A. Here,$T_A(x)$,$F_A(x)$ and

$I_A(x)$ are the real standard sets of values]0; 1^+[, i.e., $T_A(x)$: X $\rightarrow$]0; 1^+[, $I_A(x)$: X $\rightarrow$]0; 1+[, and $F_A(x)$:X $\rightarrow$]0; 1+[. The indeterminancy-value whichis also denoted by π is given by,

$$\pi_i = 1-\mu_i - \vee_i = \frac{1-\mu_i}{1+\lambda\mu_i}(or)\pi_i = 1-\mu_i - \vee_i \tag{3.4}$$

From equation (3.2),(3.3) and (3.4), a neutrosophic triplet matrix is obtained. Table 2A shows a sample tripletmatrix. Before performing clustering, triplet matrix (μ, π, $\vee$) [38] is converted into scalar value matrix using normalized hamming distance. The normalized hamming distance [39] between two locations P and Q is defined

$$N_d(P,Q) = \frac{1}{3n}\sum_{i=1}^{n}(\left|T_P(w_i - T_Q(w_i)\right| + \left|F_P(w_i - F_Q(w_i)\right| + \left|I_P(w_i - I_Q(w_i)\right|) \tag{3.5}$$

To perform the clustering part. the triplet matrix is converted into a scalar value using equation (3.5)[40]. The neutrosophic weights of a triplet matrix is converted into scalar weights. The resultant matrix is aneutrosophic matrix and HC is applied for clustering, there by we get a neutrosophic fuzzy clusters.

The dataset consists of dengue reported cases in 26 cities of Sri Lanka. Data is collected for six consecutiveyears from 2012 to 2018. First step is finding out the diatnce matrix (D) using the equation (3.1). The matrixformed here is 26×26 as distance matrix. Using equation (3.2), (3.3) and (3.4) triplet matrix of (μ, π, $\vee$) iscalculated. By using equation (3.5) the neutrosophic triplet matrix is converted to function matrix with scalarvalue upon which hierarchical clustering is formed. Example of the membership matrix obtained for different years. The representation for the year 2012 is given in table 1A.

We then perform the process of hierarchical clustering using algorithm 1, for the results diaplayed in table1A. HC is applied on each year and clusters are formed for each consecutive year from 2012 to 2018. HC hasdifferent methods such as single, complete, wighted, centroid, median and ward.

Algorithm 1: Hierarchical Clustering($N_d(P,Q)$, Method=single linkage)

```
begin
mat[][] ← initialized to N_d(P,Q) values from equation 3.5
disjoint set=[][]
for each city_i in mat[][] do
    for each city_j in mat[][] do
        n=min(max(city_i, city_j))
        merge(city_i.city_j)
    end
    repeat until single cluster
end
```

Algorithm 2: Hierarchical Clustering($N_d(P, Q)$, Method=complete linkage)

begin
mat[][] $\leftarrow$ initialized to $N_d(P, Q)$ values from equation 3.5
disjoint set=[][]
for *each* $city_i$ *in mat[][]* **do**
    for *each* $city_j$ *in mat[][]* **do**
        n=max(max($city_i, city_j$))
        merge($city_i.city_j$)
    end
    repeat until single cluster
end

In the second step, the value of falsity or the non-membership is determined using the formula (3.3). The set of values in each column of the matrix represents (μ, π, $\vee$) for each location.

Finally, the neutrosophic matrix is constructed using equation (3.4). The obtained result is a triplet of the form (0.9425, 0.0752 and 0.0603). The triplet matrix expresses the truthness, falsity and indeterminacy value of each location paired with all other locations in the dataset. Similar matrix of 26×26 is obtained for all consecutive years starting from 2012 to 2018. Now find the similarity between each pair of objects in and neutrosophic triplet matrix.

The Euclidean distance matrix, membership matrix and triplet matrix is calculated using algorithm 2. The data is taken from the year 2012 to 2017 as training data. Once the algorithm is implemented, it has to be tested for its accuracy and how well the proposed algorithm works. The process is applied on data set for the year 2018 and the clusters are formed. The predicted clusters are compared with the actual data for all the 26cities. Several performance indices techniques are elaborated in section 5.

4. Dataset Descriptions

The data is collected from Epidemiology Unit Ministry of Sri Lanka. The dengue cases are collected for six consecutive years from 2012 to 2017. The data can be downloaded from thesite [41]. Data consist of 26 locations in Sri Lanka such as Colombo, Gampaha, Kalutara, Kandy, Matale, N Eliya, Galle, Hambantota, Matara, Jaffna, Kilinochchi, Mannar, Vavuniya, Mulativu, Batticaloa, Ampara, Trincomalee, Kurunegala, Puttalam, Apura, Polonnaruwa, Badulla, Moneragala, Ratnapura, Kegalle and Kalmunai.

Table 1 List of Cities in Sri Lanka

Cities	Names
1	Colombo
2	Gampaha
3	Kalutara
4	Kandy
5	Matale
6	N Eliya
7	Galle
8	Hambantota
9	Matara
10	Jaffna
11	Kilinochchi
12	Mannar
13	Vavuniya
14	Mulativu
15	Batticola

16	Ampara
17	Trincomalee
18	Kurunegala
19	Puttalam
20	Apura
21	Polonnaruwa
22	Badulla
23	Moneragala
24	Ratnapura
25	Kegalle
26	Kalmunai

Algorithm 3: Neutrosophic Fuzzy Score Calculation

matrix[loc][loc] $\leftarrow$ initialized to distance matrix for all cities in DB
city=[list of all cities]
for *i in city* **do**
 for *j in city* **do**
  $D_{[city_i][city_j]} \leftarrow$ euclidean distance$(city_i, city_j)$
 end
end
for *i in city* **do**
 for *k in i* **do**
  for *j in city* **do**
   $x = \sum_{j=1}^{n} (D[i][k]/D[j][k])^2$
   `// n number of locations`
   $\mu_{ik} = (1/x)$
  end
 end
end
for *i in city* **do**
 for *j in city* **do**
  calculate $\vee(city_{i,j})$ using equation (3.3)
  `//` $\vee$ `is non membership value`
  calculate $\pi(city_{i,j})$ using equation (3.4)
  `//` π `is indeterminacy value`
 end
end
for *i in city* **do**
 for *j in city* **do**
  $N_d(P,Q) = \frac{1}{3n} \sum_{i=1}^{n} (\mid T_P(w_i) - T_Q(w_i) \mid + \mid T_P(w_i) - T_Q(w_i) \mid + \mid T_P(w_i) - T_Q(w_i) \mid)$
   `// hamming distance formula`
  `//` $N_d(P,Q)$ `resultant scalar matrix`
 end
end
Perform Hierarchical Clustering on $(N_d(P,Q)$, method)
`// method = (single, complete, centroid, median, ward)`
`// Perform algorithm 2 for HC`

5. Experimental Results

5.1. Inconsistency Coefficient

The relative consistency of each link in a formed hierarchical cluster is quantified as inconsistency coefficient. When the links are more consistent, the neighboring links have approximately same length. Inconsistency coefficient of each link compares its height with the average height of other links from the same level of hierarchy. When the links have larger the coefficient there exists greater the difference between the objects connected by the link. When the difference between the link values is very small, it is difficult to make conclusions. Hence higher the inconsistency gives better clustering. Inconsistency value for different links is tabulated in Table 2.

Considering the results from table 2, the maximum difference between the links in neutrosophic fuzzy hierarchical clustering is identified. When the tree is cut at maximum linkage, the resulting clusters are found to be three clusters. The number of clusters is identified using inconsistency coefficient. With the inconsistency value and the number of cluster, data is divided into three parts such as low risk, medium risk and highly affected dengue areas in Sri Lanka. Neutrosophic Fuzzy Hierarchical Clustering has shown highest inconsistent values such as **0.9168**, **0.8714**, **0.7721, 0.7428** and **0.7216** for single linkage clustering, complete linkage clustering, centroid, median and ward method respectively. The results are better in a way as NFHC has given the maximum distance between the links compared with other two techniques.

Table 2. Inconsistency Coefficient of a tree cut in Hierarchical Clustering.

	Cluster Link	**Single**	**Complete**	**Centroid**	**Median**	**Ward**
HC	I-2 links	0.7071	0.7083	0.6931	0.6682	0.6581
HC	I-3 links	**0.8913**	**0.9078**	**0.8691**	**0.7671**	**0.7891**
HC	I-4 links	0.6247	0.6901	0.5926	0.6347	0.6874
FHC	I-2 links	0.7629	0.7145	0.7526	0.6921	0.7021
FHC	I-3 links	**0.8970**	**0.8825**	**0.8191**	**0.7421**	**0.7334**
FHC	I-4 links	0.5236	0.6971	0.5626	0.6477	0.6792
NHFC	I-2 links	0.7461	0.7971	0.7526	0.7126	0.6986
NHFC	I-3 links	**0.9168**	**0.8714**	**0.7721**	**0.7428**	**0.7126**
NHFC	I-4 links	0.6326	0.5910	0.6812	0.6809	0.6574

Figure 1 depicts NFHC clustering applied on dataset for the year 2018. The value in the x-axis represents the cities and y-axis represents the tree cut. Figure 1 is visualized in shape map of Sri Lanka. Based on the inconsistency-coefficient the tree is cut into three clusters. Clustering for the year 2012-2018 is given in figure 3. It has shown effective clustering based on the performance indices explained in section 5.2.

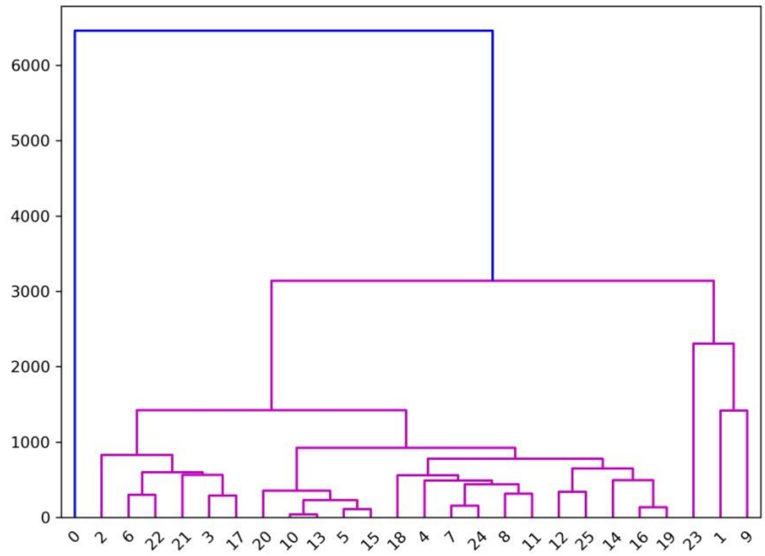


Figure 1: Dendrogram representation of NFHC on dengue data for year 2018

5.2. Performance Indices

Performance indices are used to assess clustering algorithms performance. The literature contains several performance indices. The Silhouette Coefficient [42], Davis-Bouldin (DB) index [43] and Dunn (D) index [44] are some of the most popular indicators of effectiveness assessment.

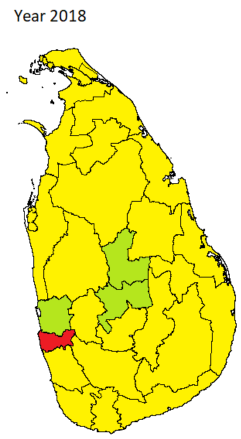


Figure 2: NFHC Cluster Visualization for Year 2018, Green-low risk, Yellow-medium risk, Red-high risk.

5.2.1. Silhouette Coefficient

Silhouettee index is an index of cluster validity used to evaluate the performance of any cluster. An element'ssilhouette index describes its proximity to its own cluster with its proximity to other clusters. A clusters silhouette width s(x) is described as,

$$s(x) = b(x) - \frac{a(x)}{\max[b(x), a(x)]} \tag{5.1}$$

where, a(x) and b(x) are the similarities of the clusters. The average silhouette width of all clusters is the silhouette index of the entire clustering. Silhouette index is used to indicate the compactness and segregation of clusters. The silhouette index value ranges from -1 to 1 and a better clustering outcome is indicated by its greater values. The silhouette coefficient of neutrosophic fuzzy hierarchical clustering is high with the value of **0.7163**, stating that the performance of Neutrosophic fuzzy hierarchical clustering is better than hierarchical clustering and fuzzy hierarchical clustering with the score of 0.6782 and 0.5137 respectively.

5.2.2. Davis-Bouldin (DB) index

The DB index is described as the cluster-to-cluster distance proportion of the amount of data. It is formulated in the following way,

$$DB = \frac{1}{c}\sum_{i-1}^{c} \max_{k \neq i}\left\{\frac{s(v_i)+s(v_k)}{d(v_i, v_k)}\right\} for 1 < i, k < c \quad (5.2)$$

The DB index seeks at minimizing cluster separation and maximizing cluster distance. The lower the DB index shows effective clustering. Our proposed algorithm Neutrosophic fuzzy hierarchical clustering has shown the lowest DB-index value of **2.5725** for the method of Single linkage clustering. Proposed algorithm has shown better results when compared to traditional algorithms. Experiment also reveals that fuzzy hierarchical clustering also performs better than traditional hierarchical clustering. However NFHC outperforms all.

5.2.3. Dunn (D) index

The D index is used to define clusters that are compact and separate. The calculation is as follows,

$$Dunn = \min_i \left\{ \min_{k \neq i} \left\{ \frac{d(v_i, v_{k)}}{\max_l s(v_l)} \right\} \right\} for 1 < k, i, l < c \quad (5.3)$$

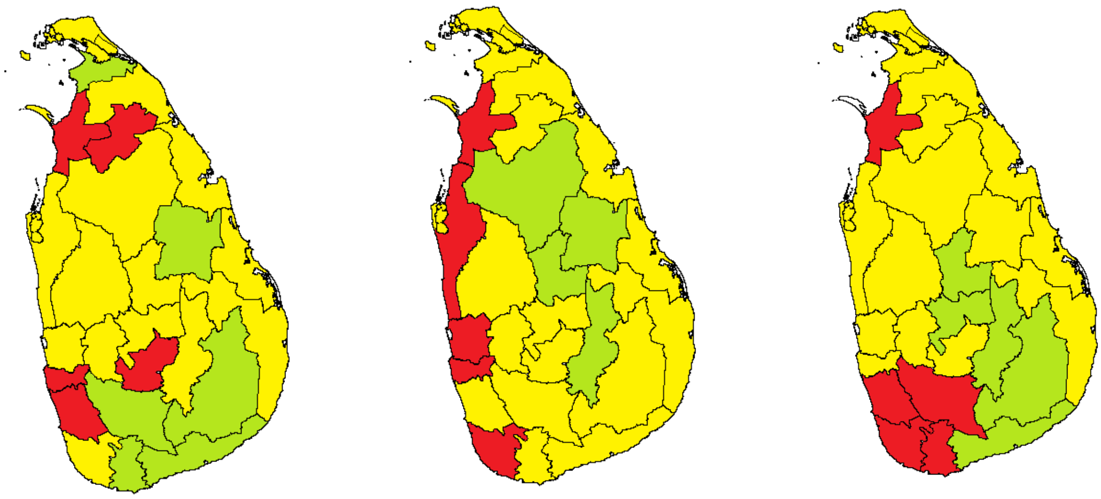
Dunn index's objective is to maximize the distance between the clusters and minimize the distance within the cluster. An elevated D index therefore means better clustering. In our implementation, highest Dunn index is achieved for NFHC algorithm with the number **1.159** of highest among all other methods. It has shown better clustering compared to other algorithms.

Table 3. Performance Metrics of HC, FHC, NFHC

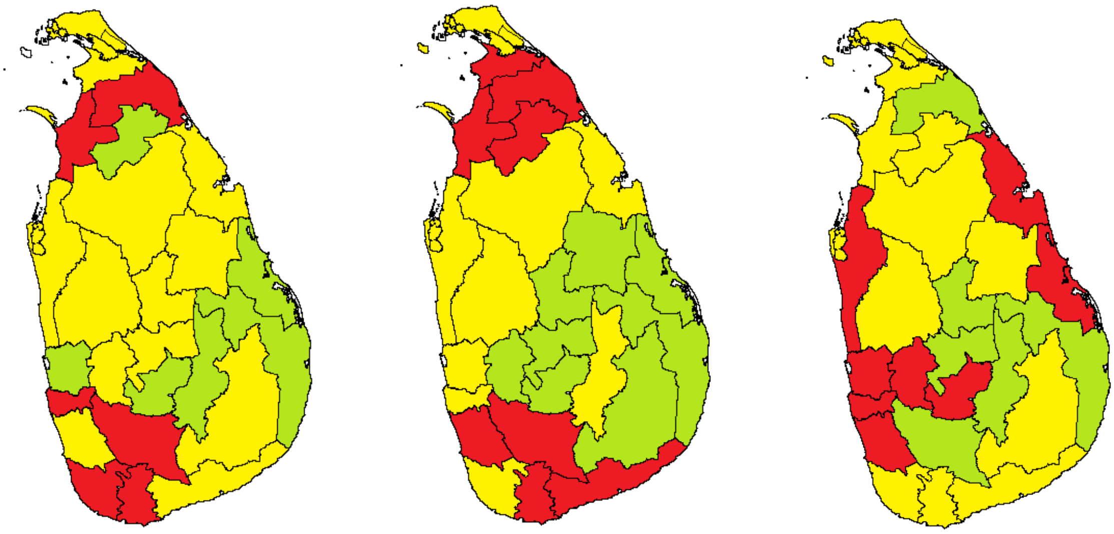
	Method	Clustering		
		HC	FHC	NHFC
Silhouette Coefficient	Single	0.1263	0.6782	**0.7163**
	Complete	0.2455	0.5763	**0.6911**
	Centroid	0.4726	0.5922	**0.6729**
	Median	0.5137	0.5501	**0.6905**
	Ward	0.4968	0.4328	**0.7077**
DB - Index	Single	5.2637	3.4266	**2.5725**
	Complete	4.1258	**2.4611**	2.4627
	Centroid	4.2162	3.1249	**2.6674**
	Median	4.5018	3.6791	**2.0169**
	Ward	4.8679	3.0628	**2.4209**
Dunn Index	Single	0.5671	0.8241	**1.134**
	Complete	0.7744	0.7689	**1.021**
	Centroid	0.8671	0.7749	**1.159**
	Median	0.9632	0.9621	**1.067**
	Ward	0.8940	0.8017	**1.116**

From table 3, we can infer that, the cluster validation of neutrosophic fuzzy hierarchical clustering has shown better results compared with hierarchical clustering and fuzzy hierarchical clustering. The metrics such as silhouette coefficient, DB index and Dunn index states the excellence of thee proposed model. The best values of silhouette cluster analysis is found in NFHC with 0.7163 for single link, 0.6911 for complete link, 0.6729 for centroid method, 0.6905 for median method and 0.7077 in ward method. Silhouette coefficient has shown highest results in NFHC for all 5 methods. DB index has also produced effective results in cluster analysis of NFHC. The lowest value of DB index is centroid method of NFHC with the value 2.6674 whereHC and FHC values for centroid method are 4.2162 and 3.1249 respectively. Other methods such as single,complete, median and ward has also given lowest values on NFHC comparing with FHC and traditional HC.Though DB index of complete method is good in FHC. FHC is also comparatively good when compared with traditional HC, as it has produced effective clustering that HC. Highest recorded Dunn index value is 1.159, for the method of centroid in NFHC. Final inference from NFHC is, it is giving better results on all the methods of clustering such as single, complete, centroid, median and ward when compared with same method on fuzzy hierarchical clustering and hierarchical clustering.

It is evident from the table 3, that the proposed NFHC shows its superiority in its performance compared to other methods. Though the fuzzy hierarchical clustering has considered membership value for clustering and produced better clusters compared with HC clusters, NFHC outperforms the fuzzy results. Thus, proposed NFHC is better in a way as it handles or capable of handling any data even with indeterminacy or inconsistency.



(a) Year 2012 (b) Year 2013 (c) Year 2014



(d) Year 2015 (e) Year 2016 (f) Year 2017

Figure 3: Cluster Plot for NFHC, color depicts Green-low risk, Yellow-medium risk, Red-high risk.

The visualization part in figure 3 clearly says that, the city of Colombo was in high risk area over the past seven years. The trend in Colombo city reveals that it is always in high risk area of dengue. In the year 2018, Colombo is the only highly affected area compared to all other cities in Sri Lanka. If the trend continues, the life of people at Colombo is in great threat. Looking into the cities in the middle of Sri Lanka such as Polonnaruwa, Matale, Polonnaruwa, Trincomalee and Kandy they have crossed the threshold of being in low risk area to medium risk area. This depicts that the states are gradually increasing in its dengue admissions. It is an important issue to be noted by the government, as in future these cities are in high risk of getting into a danger zone of dengue. Considering the southern cities of Sri Lanka, in the year 2012 the number of dengue cases was low. Over the five consecutive years it has shown the mixed results of being in medium and highly affected area. In the area of south, the control measures have to be taken strongly for cutting down the growth of dengue fever. The major pattern that is observed from the year 2012 to 2018 is that, none of the cities had reduced from reporting the dengue cases. It has always increased from one level to next level showing the spread of dengue in a drastic manner.

6. Conclusions

The study mainly identifies the areas that are affected dengue fever. Though many studies have touched the concept of clustering, the area of indeterminacy in clustering for the field of epidemiology is still under research. We used neutrosophic fuzzy hierarchical clustering and fuzzy hierarchical clustering in this article to cluster dengue fever in Sri Lanka. The purpose of neutrosophic fuzzy is, it can handle the indeterminate and inconsistent information where the fuzzy fails to handles that information. Cluster validation metrics has given better results in neutrosophic fuzzy hierarchical clustering than the other two algorithms of fuzzy hierarchical clustering and hierarchical clustering. Some of the findings from this study is that, Colombo is identified as highest dengue affected area, many of the cities are in the peak of threshold that it can move to the danger zone at any point of time. Re-emerging areas such as Galle, Matara, Hambantota, Ratnapura and Badulla are to be concentrated more so that the pattern of occurrence can be controlled in future. This method can be used in other fields so that the break out of any disease can be avoided earlier. In future, the algorithm can be extended for monitoring other diseases that are affected by environmental and climatic variables. This model can also be extended as multi-criteria model for identifying the outbreak of hotspots and early warning systems.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The following matrices contain the supplementary data for the experimental work carried out. The data is given for the year 2012.

Table A1 (a) represents Membership matrix (μ) for the cities C_1 to C_{14} from Table 1 in section 4.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
C_1	0	0.5261	0.5423	0.6631	0.6217	0.8431	0.7456	0.4675	0.7634	0.7124	0.6419	0.6787	0.7123	0.6912
C_2	0.5261	0	0.4571	0.5863	0.2413	0.7512	0.6674	0.5931	0.7213	0.8012	0.7632	0.2745	0.5481	0.8456
C_3	0.5423	0.4571	0	0.7512	0.6942	0.4623	0.7561	0.5001	0.6417	0.7812	0.4123	0.8436	0.9845	0.1664
C_4	0.6631	0.5863	0.7512	0	0.8412	0.5679	0.4987	0.6782	0.6034	0.5846	0.3699	0.7415	0.5769	0.8462
C_5	0.6217	0.2413	0.6942	0.8412	0	0.7135	0.5671	0.6746	0.5237	0.5713	0.5712	0.6716	0.9412	0.6565
C_6	0.8431	0.7512	0.4623	0.5679	0.7135	0	0.5172	0.4872	0.5716	0.4872	0.6742	0.4369	0.2145	0.7956
C_7	0.7456	0.6674	0.7561	0.4987	0.5671	0.5172	0	0.6813	0.4213	0.5716	0.7416	0.5716	0.6715	0.6135
C_8	0.4675	0.5931	0.5001	0.6782	0.6746	0.4872	0.6813	0	0.6148	0.5127	0.4137	0.8413	0.8422	0.8436
C_9	0.7634	0.7213	0.6417	0.6034	0.5237	0.5716	0.4213	0.6148	0	0.4219	0.5166	0.7168	0.6479	0.4696
C_{10}	0.7124	0.8012	0.7812	0.5846	0.5713	0.4872	0.5716	0.5127	0.4219	0	0.5712	0.6741	0.9145	0.6713
C_{11}	0.6419	0.7632	0.4123	0.3699	0.5712	0.6742	0.7416	0.4137	0.5166	0.5712	0	0.4193	0.4785	0.6971
C_{12}	0.6787	0.2745	0.8436	0.7415	0.6716	0.4369	0.5716	0.8413	0.7168	0.6741	0.4193	0	0.5136	0.8435
C_{13}	0.7123	0.5481	0.9845	0.5769	0.9412	0.2145	0.6715	0.8422	0.6479	0.9145	0.4785	0.5136	0	0.3469
C_{14}	0.6912	0.8456	0.1664	0.8462	0.6565	0.7956	0.6135	0.8436	0.4696	0.6713	0.6971	0.8435	0.3469	0

Table A1 (b) represents Membership matrix (μ) for the cities C_{15} to C_{26} from Table 1 in section 4.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
C_{15}	0.5197	0.5966	0.5523	0.8425	0.6656	0.8626	0.5946	0.6816	0.3266	0.3247	0.7486	0.9462	0.5653	0.6556
C_{16}	0.4128	0.4956	0.6595	0.5656	0.9463	0.2176	0.8956	0.6867	0.9562	0.7416	0.9512	0.6821	0.5185	0.5251
C_{17}	0.7946	0.6596	0.2648	0.8746	0.6941	0.1623	0.5952	0.7856	0.7953	0.9451	0.5623	0.1265	0.5659	0.7566
C_{18}	0.6843	0.3266	0.1654	0.6957	0.8946	0.7162	0.3266	0.2185	0.3256	0.1966	0.7152	0.3956	0.6748	0.7465
C_{19}	0.7069	0.8951	0.3261	0.2154	0.1595	0.5451	0.5482	0.1782	0.6816	0.4845	0.7185	0.3497	0.6494	0.4896
C_{20}	0.8431	0.2546	0.3665	0.5955	0.8685	0.1656	0.6595	0.8466	0.4863	0.7566	0.8465	0.6645	0.5867	0.7451
C_{21}	0.7629	0.1655	0.1796	0.6456	0.8562	0.7161	0.6845	0.7136	0.6416	0.4986	0.7856	0.7565	0.3516	0.7413
C_{22}	0.5527	0.4652	0.7656	0.5966	0.7163	0.6145	0.5164	0.5651	0.4516	0.7166	0.6146	0.3556	0.3888	0.7463
C_{23}	0.6237	0.8455	0.5965	0.7465	0.9461	0.6858	0.7465	0.8592	0.4566	0.2156	0.3562	0.4532	0.5666	0.4857
C_{24}	0.5179	0.8665	0.5165	0.6266	0.5169	0.5996	0.3566	0.7415	0.4566	0.6856	0.7164	0.5645	0.5959	0.5165
C_{25}	0.5873	0.4865	0.8698	0.7495	0.9561	0.6515	0.5795	0.5167	0.7866	0.3595	0.2186	0.8465	0.6585	0.4812
C_{26}	0.5766	0.8455	0.5356	0.5486	0.6715	0.6123	0.7155	0.4189	0.6589	0.3658	0.7529	0.6485	0.5568	0.6745

Table A1 (c) represents Membership matrix (μ) for the cities C_1 to C_{14} from Table 1 in section 4.

	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}
C_1	0.5197	0.4128	0.7946	0.6843	0.7069	0.8431	0.7629	0.5527	0.6237	0.5179	0.5873	0.5766
C_2	0.5966	0.4956	0.6596	0.3266	0.8951	0.2546	0.1655	0.4652	0.8455	0.8665	0.4865	0.8455
C_3	0.5523	0.6595	0.2648	0.1654	0.3261	0.3665	0.1796	0.7656	0.5965	0.5165	0.8698	0.5356
C_4	0.8425	0.5656	0.8746	0.6957	0.2154	0.5955	0.6456	0.5966	0.7465	0.6266	0.7495	0.5486
C_5	0.6656	0.9463	0.6941	0.8946	0.1595	0.8685	0.8562	0.7163	0.9461	0.5169	0.9561	0.6715
C_6	0.8626	0.2176	0.1623	0.7162	0.5451	0.1656	0.7161	0.6145	0.6858	0.5996	0.6515	0.6123
C_7	0.5946	0.8956	0.5952	0.3266	0.5482	0.6595	0.6845	0.5164	0.7465	0.3566	0.5795	0.7155
C_8	0.6816	0.6867	0.7856	0.2185	0.1782	0.8466	0.7136	0.5651	0.8592	0.7415	0.5167	0.4189
C_9	0.3266	0.9562	0.7953	0.3256	0.6816	0.4863	0.6416	0.4561	0.4566	0.4566	0.7866	0.6589
C_{10}	0.3247	0.7416	0.9451	0.1966	0.4845	0.7566	0.4986	0.7166	0.2156	0.6856	0.3595	0.3658
C_{11}	0.7486	0.9512	0.5623	0.7152	0.7185	0.8465	0.7856	0.6146	0.3562	0.7164	0.2186	0.7529
C_{12}	0.9462	0.6821	0.1265	0.3956	0.3497	0.6645	0.7565	0.3556	0.4532	0.5645	0.8465	0.6485
C_{13}	0.5653	0.5185	0.5659	0.6748	0.6494	0.5867	0.3516	0.3888	0.5666	0.5959	0.6585	0.5568
C_{14}	0.6556	0.5251	0.7566	0.7465	0.4896	0.7451	0.7413	0.7463	0.4857	0.5165	0.4812	0.6745

Table A1 (d) represents Membership matrix (μ) for the cities C_{15} to C_{26} from Table 1 in section 4.

	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}
C_{15}	0	0.4657	0.6289	0.6465	0.6594	0.8556	0.5162	0.3589	0.9415	0.4565	0.8465	0.7456
C_{16}	0.4657	0	0.8956	0.7441	0.8949	0.3598	0.5716	0.5635	0.4945	0.9452	0.9515	0.9512
C_{17}	0.6289	0.8956	0	0.2156	0.4163	0.6147	0.1897	0.8656	0.3859	0.1763	0.4569	0.3518
C_{18}	0.6465	0.7441	0.2156	0	0.2155	0.5716	0.7166	0.8462	0.6889	0.6455	0.5743	0.4686
C_{19}	0.6594	0.8949	0.4163	0.2155	0	0.6816	0.2965	0.4562	0.3462	0.4655	0.7152	0.8597
C_{20}	0.8556	0.3598	0.6147	0.5716	0.6816	0	0.4859	0.4856	0.5678	0.5615	0.4969	0.7456
C_{21}	0.5162	0.5716	0.1897	0.7166	0.2965	0.4859	0	0.7855	0.4887	0.7416	0.8917	0.2654
C_{22}	0.3589	0.5635	0.8656	0.8462	0.4562	0.4856	0.7855	0	0.8946	0.4852	0.1985	0.6464
C_{23}	0.9415	0.4945	0.3859	0.6889	0.3462	0.5678	0.4887	0.8946	0	0.8561	0.5785	0.4156
C_{24}	0.4565	0.9452	0.1763	0.6455	0.4655	0.5615	0.7416	0.4852	0.8561	0	0.4668	0.5486
C_{25}	0.8465	0.9515	0.4569	0.5743	0.7152	0.4969	0.8917	0.1985	0.5785	0.4668	0	0.5972
C_{26}	0.7456	0.9512	0.3518	0.4686	0.8597	0.7456	0.2654	0.6464	0.4156	0.5486	0.5972	0

Table A2 (a) represents Neutrosophic matrix (μ, π, $\vee$) for the cities C_1 to C_5 from Table 1 in section 4.

	C_1	C_2	C_3	C_4	C_5
C_1	0,0,0	0.5261,0.1403,0.3335	0.5423,0.1384,0.3192	0.6631,0.1068,0.2300	0.6217,0.1256,0.2526
C_2	0.5261,0.1403,0.3335	0,0,0	0.4571,0.1316,0.4112	0.5863,0.1203,0.2933	0.2413,0.1096,0.6491
C_3	0.5423,0.1384,0.3192	0.4571,0.1316,0.4112	0,0,0	0.7512,0.0857,0.1630	0.6942,0.1000,0.2057
C_4	0.6631,0.1068,0.2300	0.5863,0.1203,0.2933	0.7512,0.0857,0.1630	0,0,0	0.8412,0.0588,0.0999
C_5	0.6217,0.1256,0.2526	0.2413,0.1091,0.6491	0.6942,0.1000,0.2057	0.8412,0.0588,0.0999	0,0,0

Table A2 (b) represents Neutrosophic matrix (μ, π, $\vee$) for the cities C_6 to C_{10} from Table 1 in section 4.

	C_1	C_2	C_3	C_4	C_5
C_6	0.8431,0.0631,0.0937	0.7512,0.0857,0.1630	0.4623,0.1314,0.4062	0.5679,0.1229,0.3091	0,0,0
C_7	0.7456,0.0950,0.1593	0.6674,0.1059,0.2266	0.7561,0.0844,0.1594	0.4987,0.1297,0.3715	0.7135,0.0954,0.1910
C_8	0.4675,0.1449,0.3875	0.5931,0.1193,0.2875	0.5001,0.1296,0.3702	0.6782,0.1035,0.2182	0.5671,0.1230,0.3098
C_9	0.7634,0.0897,0.1468	0.7213,0.0935,0.1851	0.6417,0.1110,0.2472	0.6034,0.1177,0.2788	0.6746,0.10439,0.2210
C_{10}	0.7124,0.1044,0.1831	0.8012,0.0714,0.1273	0.7812,0.0773,0.1414	0.5846,0.1206,0.2947	0.5237,0.1277,0.3485

Table A2 (c) represents Neutrosophic matrix (μ, π, ∨) for the cities C_{11} to C_{20} from Table 1 in section 4.

	C_1	C_2	C_3	C_4	C_5
C_{11}	0.6419,0.1214,0.2366	0.7632,0.0824,0.1543	0.4123,0.1316,0.4560	0.3699,0.1295,0.5005	0.5712,0.1224,0.3063
C_{12}	0.6787,0.1130,0.2082	0.2745,0.1169,0.6085	0.8436,0.0580,0.0983	0.7415,0.0883,0.1701	0.6716,0.1050,0.2233
C_{13}	0.7123,0.1047,0.1832	0.5481,0.1253,0.3265	0.9845,0.0063,0.0091	0.5769,0.1217,0.3013	0.9412,0.0233,0.0354
C_{14}	0.6912,0.1099,0.1988	0.8456,0.0574,0.0969	0.1664,0.0869,0.7466	0.8462,0.0572,0.0965	0.6565,0.1081,0.2353
C_{15}	0.5197,0.1410,0.3392	0.5966,0.1188,0.2845	0.5523,0.1248,0.3228	0.8425,0.0584,0.0990	0.6656,0.1062,0.2281
C_{16}	0.4128,0.1457,0.4414	0.4956,0.1299,0.3744	0.6595,0.1075,0.2329	0.5656,0.1232,0.3111	0.9463,0.0213,0.0323
C_{17}	0.7946,0.0798,0.1255	0.6596,0.1075,0.2328	0.2648,0.1149,0.6202	0.8746,0.0476,0.0777	0.6941,0.1000,0.2058
C_{18}	0.6843,0.1116,0.2040	0.3266,0.1253,0.5480	0.1654,0.0866,0.7479	0.6957,0.0996,0.2046	0.8946,0.0405,0.0648
C_{19}	0.7069,0.1058,0.1872	0.8951,0.0404,0.0644	0.3261,0.1252,0.5486	0.2154,0.1028,0.6817	0.1595,0.0844,0.7560
C_{20}	0.8431,0.0631,0.0937	0.2546,0.1127,0.6326	0.3665,0.1293,0.5041	0.5955,0.1190,0.2854	0.8685,0.0497,0.0817

Table A2 (d) represents Neutrosophic matrix (μ, π, ∨) for the cities C_{21} to C_{26} from Table 1 in section 4.

	C_1	C_2	C_3	C_4	C_5
C_{21}	0.7629,0.0898,0.1472	0.1655,0.0866,0.7478	0.1796,0.0916,0.7287	0.6456,0.1103,0.2440	0.8562,0.0538,0.0899
C_{22}	0.5527,0.1371,0.3101	0.4652,0.1313,0.4034	0.7656,0.0817,0.1526	0.5966,0.1188,0.2845	0.7163,0.0947,0.1889
C_{23}	0.6237,0.1252,0.2510	0.8455,0.0574,0.0970	0.5965,0.1188,0.2846	0.7465,0.0870,0.1664	0.9461,0.0214,0.0324
C_{24}	0.5179,0.1412,0.3408	0.8665,0.0504,0.0830	0.5165,0.1283,0.3551	0.6266,0.1138,0.2595	0.5169,0.1283,0.3547
C_{25}	0.5873,0.1319,0.2807	0.4865,0.1304,0.3830	0.8698,0.0492,0.0809	0.7495,0.0861,0.1643	0.9561,0.0176,0.0262
C_{26}	0.5766,0.1336,0.2897	0.8455,0.0574,0.0970	0.5356,0.1266,0.3377	0.5486,0.1252,0.3261	0.6715,0.1050,0.2234

Table A2 (e) represents Neutrosophic matrix (μ, π, ∨) for the cities C_1 to C_5 from Table 1 in section 4.

	C_6	C_7	C_8	C_9	C_{10}
C_1	0.8431,0.0582,0.0986	0.7456,0.0872,0.1671	0.4675,0.1312,0.4012	0.7634,0.0824,0.1541	0.7124,0.0956,0.1919
C_2	0.7512,0.0857,0.1630	0.6674,0.1059,0.2266	0.5931,0.1193,0.2875	0.7213,0.0935,0.1851	0.8012,0.0714,0.1273
C_3	0.4623,0.1314,0.4062	0.7561,0.0844,0.1594	0.5001,0.1296,0.3702	0.6417,0.1110,0.2472	0.7812,0.0773,0.1414
C_4	0.5679,0.1229,0.3091	0.4987,0.1297,0.3715	0.6782,0.1035,0.2182	0.6034,0.1177,0.2788	0.5846,0.1206,0.2947
C_5	0.7135,0.0954,0.1910	0.5671,0.1230,0.3098	0.6746,0.1043,0.2210	0.5237,0.1277,0.3485	0.5713,0.1224,0.3062

Table A2 (f) represents Neutrosophic matrix (μ, π, ∨) for the cities C_6 to C_{10} from Table 1 in section 4.

	C_6	C_7	C_8	C_9	C_{10}
C_6	0,0,0	0.5172,0.1283,0.3544	0.4872,0.1304,0.3823	0.5716,0.1224,0.3059	0.4872,0.1304,0.3823
C_7	0.5172,0.1283,0.3544	0,0,0	0.6813,0.1029,0.2157	0.4213,0.1320,0.4469	0.5716,0.1224,0.3059
C_8	0.4872,0.1304,0.3823	0.6813,0.1029,0.2157	0,0,0	0.6148,0.1158,0.2693	0.5127,0.1286,0.3586
C_9	0.5716,0.1224,0.3059	0.4213,0.1320,0.4469	0.6148,0.1158,0.2693	0,0,0	0.4219,0.1327,0.4462
C_{10}	0.4872,0.1304,0.3823	0.5716,0.1224,0.3059	0.5127,0.1286,0.3586	0.4219,0.1327,0.4462	0,0,0

Table A2 (g) represents Neutrosophic matrix (μ, π, ∨) for the cities C_{11} to C_{20} from Table 1 in section 4.

	C_6	C_7	C_8	C_9	C_{10}
C_{11}	0.6742,0.1044,0.2213	0.7416,0.0883,0.1700	0.4137,0.1316,0.4546	0.5166,0.1283,0.3550	0.3368,0.1265,0.5366
C_{12}	0.4369,0.1318,0.4312	0.5716,0.1224,0.3059	0.8413,0.0588,0.0998	0.7168,0.0946,0.1885	0.6741,0.1044,0.2215
C_{13}	0.2145,0.1025,0.6829	0.6715,0.1050,0.2234	0.8422,0.0585,0.0992	0.6479,0.1098,0.2422	0.9145,0.0333,0.0521
C_{14}	0.7956,0.0731,0.1312	0.6135,0.1838,0.2703	0.8436,0.0580,0.0983	0.4696,0.1312,0.3991	0.6713,0.1050,0.2236
C_{15}	0.8626,0.0517,0.0856	0.5946,0.1191,0.2862	0.6816,0.1028,0.2155	0.3266,0.1253,0.5480	0.3247,0.1250,0.5502
C_{16}	0.2176,0.1034,0.6789	0.8956,0.0402,0.0641	0.6867,0.1017,0.2115	0.9562,0.0175,0.0262	0.7416,0.0883,0.1700
C_{17}	0.1623,0.0854,0.7522	0.5952,0.1190,0.2857	0.7856,0.0760,0.1383	0.7953,0.0732,0.1314	0.9451,0.0218,0.0330
C_{18}	0.7162,0.0947,0.1890	0.3266,0.1253,0.5480	0.2185,0.1036,0.6778	0.3256,0.1251,0.5492	0.1966,0.0971,0.7062
C_{19}	0.5451,0.1256,0.3292	0.5482,0.1252,0.3265	0.1782,0.0911,0.7306	0.6816,0.1028,0.2155	0.4845,0.1305,0.3849
C_{20}	0.1656,0.0866,0.7477	0.6595,0.1075,0.2329	0.8466,0.0570,0.0963	0.4863,0.1304,0.3832	0.7566,0.0842,0.1591

Table A2 (h) represents Neutrosophic matrix $(\mu, \pi, \vee)$ for the cities C_{21} to C_{26} from Table 1 in section 4.

	C_6	C_7	C_8	C_9	C_{10}
C_{21}	0.7161,0.0947,0.1891	0.6845,0.1022,0.2132	0.7136,0.0954,0.1909	0.6416,0.1110,0.2473	0.4986,0.1297,0.3716
C_{22}	0.6145,0.1159,0.2695	0.5164,0.1283,0.3552	0.5651,0.1232,0.3116	0.4516,0.1317,0.4166	0.7166,0.0946,0.1887
C_{23}	0.6858,0.1019,0.2122	0.7465,0.0870,0.1664	0.8592,0.0528,0.0879	0.4566,0.1316,0.4117	0.2156,0.1028,0.6815
C_{24}	0.5996,0.1183,0.2820	0.3566,0.1285,0.5148	0.7415,0.0883,0.1701	0.4566,0.1316,0.4117	0.6856,0.1019,0.2124
C_{25}	0.6515,0.1091,0.2393	0.5795,0.1213,0.2991	0.5167,0.1283,0.3549	0.7866,0.0757,0.1376	0.3595,0.1287,0.5117
C_{26}	0.6123,0.1163,0.2713	0.7155,0.0949,0.1895	0.4189,0.1317,0.4493	0.6589,0.1076,0.2334	0.3658,0.1292,0.5049

Table A2 (i) represents Neutrosophic matrix $(\mu, \pi, \vee)$ for the cities C_1 to C_5 from Table 1 in section 4.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_1	0.6419,0.1110,0.2470	0.6787,0.1034,0.2178	0.7123,0.0960,0.1919	0.6912,0.1006,0.2081	0.5197,0.12811,0.3521
C_2	0.7632,0.0824,0.1543	0.2745,0.1169,0.6085	0.5481,0.1253,0.3265	0.8456,0.0574,0.0969	0.5966,0.1188,0.2845
C_3	0.4123,0.1316,0.4560	0.8436,0.0580,0.0983	0.9845,0.0063,0.0091	0.1664,0.0869,0.7466	0.5523,0.1248,0.3228
C_4	0.3699,0.1295,0.5005	0.7415,0.0883,0.1701	0.5769,0.1217,0.3013	0.8462,0.0572,0.0965	0.8425,0.0584,0.0990
C_5	0.5712,0.1224,0.3063	0.6716,0.1050,0.2233	0.9412,0.0233,0.0354	0.6565,0.1081,0.2353	0.6656,0.1062,0.2281

Table A2 (j) represents Neutrosophic matrix $(\mu, \pi, \vee)$ for the cities C_6 to C_{10} from Table 1 in section 4.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_6	0.6742,0.1044,0.2213	0.4369,0.1318,0.4312	0.2145,0.1025,0.6829	0.7956,0.0731,0.1312	0.8626,0.0517,0.0856
C_7	0.7416,0.0883,0.1700	0.5716,0.1224,0.3059	0.6715,0.1050,0.2234	0.6135,0.1838,0.2703	0.5946,0.1191,0.2862
C_8	0.4137,0.1316,0.4546	0.8413,0.0588,0.0998	0.8422,0.0585,0.0992	0.8436,0.0580,0.0983	0.6816,0.1028,0.2155
C_9	0.5166,0.1283,0.3550	0.7168,0.0946,0.1885	0.6479,0.1098,0.2422	0.4696,0.1312,0.3991	0.3266,0.1253,0.5480
C_{10}	0.5712,0.1224,0.3063	0.6741,0.1044,0.2214	0.9145,0.0333,0.0521	0.6713,0.1050,0.2236	0.3247,0.1250,0.5502

Table A2 (k) represents Neutrosophic matrix $(\mu, \pi, \vee)$ for the cities C_{11} to C_{20} from Table 1 in section 4.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_{11}	0,0,0	0.4193,0.1317,0.4489	0.4785,0.1308,0.3906	0.6971,0.0993,0.2035	0.7486,0.0864,0.1649
C_{12}	0.4193,0.1317,0.4489	0,0,0	0.5136,0.1286,0.3577	0.8435,0.0581,0.0983	0.9462,0.0214,0.0323
C_{13}	0.4785,0.1308,0.3906	0.5136,0.1286,0.3577	0,0,0	0.3469,0.1276,0.5254	0.5653,0.1232,0.3114
C_{14}	0.6971,0.0993,0.2035	0.8435,0.0581,0.0983	0.3469,0.1276,0.5254	0,0,0	0.6556,0.1083,0.2360
C_{15}	0.7486,0.0864,0.1649	0.9462,0.0214,0.0323	0.5653,0.1232,0.3114	0.6556,0.1083,0.2360	0,0,0
C_{16}	0.9512,0.0195,0.0292	0.6821,0.1027,0.2151	0.5185,0.1282,0.3532	0.5251,0.1276,0.3472	0.4657,0.1313,0.4029
C_{17}	0.5623,0.1236,0.3140	0.1265,0.0710,0.8024	0.5659,0.1231,0.3109	0.7566,0.0842,0.1591	0.6289,0.1134,0.2576
C_{18}	0.7152,0.0950,0.1897	0.3956,0.1310,0.4733	0.6748,0.1043,0.2208	0.7465,0.0870,0.1664	0.6465,0.1101,0.2433
C_{19}	0.7185,0.0942,0.1872	0.3497,0.1278,0.5224	0.6494,0.1095,0.2410	0.4896,0.1302,0.3801	0.6594,0.1075,0.2330
C_{20}	0.8465,0.0571,0.0963	0.6645,0.1065,0.2289	0.5867,0.1203,0.2929	0.7451,0.0873,0.1675	0.8556,0.0540,0.0903

Table A2 (l) represents Neutrosophic matrix $(\mu, \pi, \vee)$ for the cities C_{21} to C_{26} from Table 1 in section 4.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}
C_{21}	0.7856,0.0760,0.1383	0.7565,0.0843,0.1591	0.3516,0.1280,0.5203	0.7413,0.0883,0.1703	0.5162,0.1284,0.3553
C_{22}	0.6146,0.1159,0.2694	0.3556,0.1284,0.5159	0.3888,0.1307,0.4804	0.7463,0.0870,0.1666	0.3589,0.1287,0.5123
C_{23}	0.3562,0.1284,0.5153	0.4532,0.1316,0.4151	0.5666,0.1230,0.3103	0.4857,0.1304,0.3838	0.9415,0.0232,0.0352
C_{24}	0.7164,0.0947,0.1888	0.5645,0.1233,0.3121	0.5959,0.1189,0.2851	0.5165,0.1283,0.3551	0.4565,0.1316,0.4118
C_{25}	0.2186,0.1037,0.6776	0.8465,0.0571,0.0963	0.6585,0.1077,0.2337	0.4812,0.1307,0.3880	0.8465,0.0571,0.0963
C_{26}	0.7529,0.0852,0.1618	0.6485,0.1097,0.2417	0.5568,0.1242,0.3189	0.6745,0.1043,0.2211	0.7456,0.0872,0.1671

Table A2 (m) represents Neutrosophic matrix (μ, π, $\vee$) for the cities C_1 to C_5 from Table 1 in section 4.

	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}
C_1	0.4128,0.1316,0.4555	0.7946,0.07341,0.1319	0.6843,0.1022,0.2134	0.7069,0.0970,0.1960	0.8431,0.0582,0.0986
C_2	0.4956,0.1299,0.3744	0.6596,0.1075,0.2328	0.3266,0.1253,0.5480	0.8951,0.0404,0.0644	0.2546,0.1127,0.6326
C_3	0.6595,0.1075,0.2329	0.2648,0.1149,0.6202	0.1654,0.0866,0.7479	0.3261,0.1252,0.5486	0.3665,0.1293,0.5041
C_4	0.5656,0.1232,0.3111	0.8746,0.0476,0.0777	0.6957,0.0996,0.2046	0.2154,0.1028,0.6817	0.5955,0.1190,0.2854
C_5	0.9463,0.0213,0.0323	0.6941,0.1000,0.2058	0.8946,0.0405,0.0648	0.1595,0.0844,0.7560	0.8685,0.0497,0.0817

Table A2 (n) represents Neutrosophic matrix (μ, π, $\vee$) for the cities C_6 to C_{10} from Table 1 in section 4.

	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}
C_6	0.2176,0.1034,0.6789	0.1623,0.0854,0.7522	0.7162,0.0947,0.1890	0.5451,0.1256,0.3292	0.1656,0.0866,0.7477
C_7	0.8956,0.0402,0.0641	0.5952,0.1190,0.2857	0.3266,0.1253,0.5480	0.5482,0.1252,0.3265	0.6595,0.1075,0.2329
C_8	0.6867,0.1017,0.2115	0.7856,0.0760,0.1383	0.2185,0.1036,0.6778	0.1782,0.0911,0.7306	0.8466,0.0570,0.0963
C_9	0.9562,0.0175,0.0262	0.7953,0.0732,0.1314	0.3256,0.1251,0.5492	0.6816,0.1028,0.2155	0.4863,0.1304,0.3832
C_{10}	0.7416,0.0883,0.1700	0.9451,0.0218,0.0330	0.1966,0.0971,0.7062	0.4845,0.1305,0.3849	0.7566,0.0842,0.1591

Table A2 (o) represents Neutrosophic matrix (μ, π, $\vee$) for the cities C_{11} to C_{15} from Table 1 in section 4.

	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}
C_{11}	0.9512,0.0195,0.0292	0.5623,0.1236,0.3140	0.7152,0.0950,0.1897	0.7185,0.0942,0.1872	0.8465,0.0571,0.0963
C_{12}	0.6821,0.1027,0.2151	0.1265,0.0710,0.8024	0.3956,0.1310,0.4733	0.3497,0.1278,0.5224	0.6645,0.1065,0.2289
C_{13}	0.5185,0.1282,0.3532	0.5659,0.1231,0.3109	0.6748,0.1043,0.2208	0.6494,0.1095,0.2410	0.5867,0.1203,0.2929
C_{14}	0.5251,0.1276,0.3472	0.7566,0.0842,0.1591	0.7465,0.0870,0.1664	0.4896,0.1302,0.3801	0.7451,0.0873,0.1675
C_{15}	0.4657,0.1313,0.4029	0.6289,0.1134,0.2576	0.6465,0.1101,0.2433	0.6594,0.1075,0.2330	0.8556,0.0540,0.0903
C_{16}	0,0,0	0.8956,0.0402,0.0641	0.7441,0.0876,0.1682	0.8949,0.0404,0.0646	0.3598,0.1288,0.5113
C_{17}	0.8956,0.0402,0.0641	0,0,0	0.2156,0.1028,0.6815	0.4163,0.1317,0.4519	0.6147,0.1159,0.2693
C_{18}	0.7441,0.0876,0.1682	0.2156,0.1028,0.6815	0,0,0	0.2155,0.1028,0.6816	0.5716,0.1224,0.3059
C_{19}	0.8949,0.0404,0.0646	0.4163,0.1317,0.4519	0.2155,0.1028,0.6816	0,0,0	0.6816,0.1028,0.2155
C_{20}	0.3598,0.1288,0.5113	0.6147,0.1159,0.2693	0.5716,0.1224,0.3059	0.6816,0.1028,0.2155	0,0,0

Table A2 (p) represents Neutrosophic matrix (μ, π, $\vee$) for the cities C_{21} to C_{26} from Table 1 in section 4.

	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}
C_{21}	0.5716,0.1224,0.3059	0.1897,0.0949,0.7153	0.7166,0.0946,0.1887	0.2965,0.1209,0.5825	0.4859,0.1304,0.3836
C_{22}	0.5635,0.1234,0.3130	0.8656,0.0507,0.0836	0.8462,0.0572,0.0965	0.4562,0.1316,0.4121	0.4856,0.1304,0.3839
C_{23}	0.4945,0.1299,0.3755	0.3859,0.1306,0.4834	0.6889,0.1012,0.2098	0.3462,0.1275,0.5262	0.5678,0.1229,0.3092
C_{24}	0.9452,0.0218,0.0329	0.1763,0.0904,0.7332	0.6455,0.1103,0.2441	0.4655,0.1313,0.4031	0.5615,0.1237,0.3147
C_{25}	0.9515,0.0193,0.0291	0.4569,0.1316,0.4114	0.5743,0.1220,0.3036	0.7152,0.0950,0.1897	0.4969,0.1298,0.3732
C_{26}	0.9512,0.0195,0.0292	0.3518,0.1280,0.5201	0.4686,0.1312,0.4001	0.8597,0.0527,0.0875	0.7456,0.0872,0.1671

Table A2 (q) represents Neutrosophic matrix (μ, π, $\vee$) for the cities C_1 to C_5 from Table 1 in section 4.

	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}
C_1	0.7629,0.0825,0.1545	0.5527,0.1247,0.3225	0.6237,0.1143,0.2619	0.5179,0.1282,0.3538	0.5873,0.1202,0.2924	0.5766,0.1217,0.3016
C_2	0.1655,0.0866,0.7478	0.4652,0.1313,0.4034	0.8455,0.0574,0.0970	0.8665,0.0504,0.0830	0.4865,0.1304,0.3830	0.8455,0.0574,0.0970
C_3	0.1796,0.0916,0.7287	0.7656,0.0817,0.1526	0.5965,0.1188,0.2846	0.5165,0.1283,0.3551	0.8698,0.0492,0.0809	0.5356,0.1266,0.3377
C_4	0.6456,0.1103,0.2440	0.5966,0.1188,0.2845	0.7465,0.0870,0.1664	0.6266,0.1138,0.2595	0.7495,0.0861,0.1643	0.5486,0.1252,0.3261
C_5	0.8562,0.0538,0.0899	0.7163,0.0947,0.1889	0.9461,0.0214,0.0324	0.5169,0.1283,0.3547	0.9561,0.0176,0.0262	0.6715,0.1050,0.2234

Table A2 (r) represents Neutrosophic matrix (μ, π, ∨) for the cities C_6 to C_{10} from Table 1 in section 4.

	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}
C_6	0.7161,0.0947,0.1891	0.6145,0.1159,0.2695	0.6858,0.1019,0.2122	0.5996,0.1183,0.2820	0.6515,0.1091,0.2393	0.6123,0.1163,0.2713
C_7	0.6845,0.1022,0.2132	0.5164,0.1283,0.3552	0.7465,0.0870,0.1664	0.3566,0.1285,0.5148	0.5795,0.1213,0.2991	0.7155,0.0949,0.1895
C_8	0.7136,0.0954,0.1909	0.5651,0.1232,0.3116	0.8592,0.0528,0.0879	0.7415,0.0883,0.1701	0.5167,0.1283,0.3549	0.4189,0.1317,0.4493
C_9	0.6416,0.1110,0.2473	0.4561,0.1316,0.4122	0.4566,0.1316,0.4117	0.4566,0.1316,0.4117	0.7866,0.0757,0.1376	0.6589,0.1076,0.2334
C_{10}	0.4986,0.1297,0.3716	0.7166,0.0946,0.1887	0.2156,0.1028,0.6815	0.6856,0.1019,0.2124	0.3595,0.1287,0.5117	0.3658,0.1292,0.5049

Table A2 (s) represents Neutrosophic matrix (μ, π, ∨) for the cities C_{11} to C_{20} from Table 1 in section 4.

	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}
C_{11}	0.7856,0.0760,0.1383	0.6146,0.1159,0.2694	0.3562,0.1284,0.5153	0.7164,0.0947,0.1888	0.2186,0.1037,0.6776	0.7529,0.0852,0.1618
C_{12}	0.7565,0.0843,0.1591	0.3556,0.1284,0.5159	0.4532,0.1316,0.4151	0.5645,0.1233,0.3121	0.8465,0.0571,0.0963	0.6485,0.1097,0.2417
C_{13}	0.3516,0.1280,0.5203	0.3888,0.1307,0.4804	0.5666,0.1230,0.3103	0.5959,0.1189,0.2851	0.6585,0.1077,0.2337	0.5568,0.1242,0.3189
C_{14}	0.7413,0.0883,0.1703	0.7463,0.0870,0.1666	0.4857,0.1304,0.3838	0.5165,0.1283,0.3551	0.4812,0.1307,0.3880	0.6745,0.1043,0.2211
C_{15}	0.5162,0.1284,0.3553	0.3589,0.1287,0.5123	0.9415,0.0232,0.0352	0.4565,0.1316,0.4118	0.8465,0.0571,0.0963	0.7456,0.0872,0.1671
C_{16}	0.5716,0.1224,0.3059	0.5635,0.1234,0.3130	0.4945,0.1299,0.3755	0.9452,0.0218,0.0329	0.9515,0.0193,0.0291	0.9512,0.0195,0.0292
C_{17}	0.1897,0.0949,0.7153	0.8656,0.0507,0.0836	0.3859,0.1306,0.4834	0.1763,0.0904,0.7332	0.4569,0.1316,0.4114	0.3518,0.1280,0.5201
C_{18}	0.7166,0.0946,0.1887	0.8462,0.0572,0.0965	0.6889,0.1012,0.2098	0.6455,0.1103,0.2441	0.5743,0.1220,0.3036	0.4686,0.1312,0.4001
C_{19}	0.2965,0.1209,0.5825	0.4562,0.1316,0.4121	0.3462,0.1275,0.5262	0.4655,0.1313,0.4031	0.7152,0.0950,0.1897	0.8597,0.0527,0.0875
C_{20}	0.4859,0.1304,0.3836	0.4856,0.1304,0.3839	0.5678,0.1229,0.3092	0.5615,0.1237,0.3147	0.4969,0.1298,0.3732	0.7456,0.0872,0.1671

Table A2 (t) represents Neutrosophic matrix (μ, π, ∨) for the cities C_{21} to C_{26} from Table 1 in section 4.

	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}
C_{21}	0,0,0	0.7855,0.0760,0.1384	0.4887,0.1303,0.3809	0.7416,0.0883,0.1700	0.8917,0.0416,0.0666	0.2654,0.1150,0.6195
C_{22}	0.7855,0.0760,0.1384	0,0,0	0.8946,0.0405,0.0648	0.4852,0.1305,0.3842	0.1985,0.0977,0.7037	0.6464,0.1101,0.2434
C_{23}	0.4887,0.1303,0.3809	0.8946,0.0405,0.0648	0,0,0	0.8561,0.0539,0.0899	0.5785,0.1214,0.3000	0.4156,0.1316,0.4527
C_{24}	0.7416,0.08830.1700	0.4852,0.1305,0.3842	0.8561,0.0539,0.0899	0,0,0	0.4668,0.1313,0.4018	0.5486,0.1252,0.3261
C_{25}	0.8917,0.0416,0.0666	0.1985,0.0977,0.7037	0.5785,0.1214,0.3000	0.4668,0.1313,0.4018	0,0,0	0.5972,0.1187,0.2840
C_{26}	0.2654,0.1150,0.6195	0.6464,0.1101,0.2434	0.4156,0.1316,0.4527	0.5486,0.1252,0.3261	0.5972,0.1187,0.2840	0,0,0

Table A3 (a) represents Neutrosophic matrix after applying hamming distance for the cities C_1 to C_{14} from Table 1 in section 4.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
C_1	0	0.4433	0.447	0.5418	0.3582	0.7898	0.5508	0.3305	0.3261	0.6694	0.5571	0.271	0.3458	0.1396
C_2	0.4433	0	0.3353	0.1916	0.1823	0.5309	0.1945	0.1967	0.2858	0.7518	0.4687	0.5588	0.539	0.4353
C_3	0.447	0.3353	0	0.3313	0.4457	0.2289	0.6479	0.2153	0.2834	0.4965	0.6412	0.4136	0.6892	0.6917
C_4	0.5418	0.1916	0.3313	0	0.7432	0.5929	0.5827	0.1459	0.3221	0.6101	0.1763	0.14	0.3278	0.5817
C_5	0.3582	0.1823	0.4457	0.7432	0	0.6959	0.2846	0.5782	0.2531	0.4157	0.3157	0.341	0.5521	0.5674
C_6	0.7898	0.5309	0.2289	0.5929	0.6959	0	0.34	0.2859	0.3219	0.6197	0.7082	0.6185	0.61	0.7526
C_7	0.5508	0.1945	0.6479	0.5827	0.2846	0.34	0	0.3838	0.5086	0.1929	0.2141	0.6446	0.1398	0.26548
C_8	0.3305	0.1967	0.2153	0.1459	0.5782	0.2859	0.3838	0	0.3662	0.1384	0.2855	0.1762	0.4473	0.663
C_9	0.3261	0.2858	0.2834	0.3221	0.2531	0.3219	0.5086	0.3662	0	0.7778	0.498	0.4885	0.3933	0.3152
C_{10}	0.6694	0.7518	0.4965	0.6101	0.4157	0.6197	0.1929	0.1384	0.7778	0	0.604	0.5562	0.7577	0.5133
C_{11}	0.5571	0.4687	0.6412	0.1763	0.3157	0.7082	0.2141	0.2855	0.498	0.604	0	0.4959	0.469	0.1715
C_{12}	0.271	0.5588	0.4136	0.14	0.341	0.6185	0.6446	0.1762	0.4885	0.5562	0.4959	0	0.7279	0.6924
C_{13}	0.3458	0.539	0.6892	0.3278	0.5521	0.61	0.1398	0.4473	0.3933	0.7577	0.469	0.7279	0	0.7494
C_{14}	0.1396	0.4353	0.6917	0.5817	0.5674	0.7526	0.2654	0.663	0.3152	0.5133	0.1715	0.6924	0.7494	0

Table A3 (b) represents Neutrosophic matrix after applying hamming distance for the cities C_{15} to C_{26} from Table 1 in section 4.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
C_{15}	0.6944	0.7008	0.4806	0.4121	0.1509	0.79	0.4049	0.6515	0.3032	0.5141	0.3544	0.5558
C_{16}	0.4426	0.6747	0.44	0.7544	0.3789	0.1483	0.5688	0.3143	0.2569	0.1429	0.4367	0.7575
C_{17}	0.3075	0.548	0.3728	0.1853	0.1045	0.3206	0.7626	0.7373	0.1398	0.3686	0.7656	0.7036
C_{18}	0.5409	0.2148	0.2086	0.1	0.6134	0.4225	0.1798	0.717	0.1925	0.665	0.7401	0.7935
C_{19}	0.591	0.7089	0.4751	0.3052	0.1797	0.3776	0.1955	0.2037	0.4955	0.212	0.7846	0.39
C_{20}	0.2562	0.3649	0.2452	0.3967	0.3969	0.4713	0.5398	0.103	0.1251	0.1014	0.36	0.4607
C_{21}	0.3619	0.2825	0.7845	0.1805	0.5186	0.3665	0.1048	0.6383	0.1369	0.1912	0.1633	0.1431
C_{22}	0.481	0.3809	0.6533	0.7111	0.3088	0.5711	0.113	0.1428	0.4441	0.5196	0.5764	0.6453
C_{23}	0.4514	0.7166	0.6064	0.3478	0.7938	0.4129	0.5549	0.6055	0.1707	0.5102	0.3787	0.5538
C_{24}	0.5419	0.1217	0.6572	0.5024	0.4357	0.5537	0.5498	0.318	0.3079	0.7958	0.6032	0.7631
C_{25}	0.4644	0.7398	0.1996	0.4928	0.5413	0.6671	0.2003	0.2952	0.4742	0.5949	0.4601	0.2854
C_{26}	0.7894	0.746	0.2488	0.3585	0.6353	0.6826	0.6129	0.539	0.6214	0.4399	0.345	0.6074

Table A3 (c) represents Neutrosophic matrix after applying hamming distance for the cities C_1 to C_{14} from Table 1 in section 4.

	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}
C_1	0.6944	0.4426	0.3075	0.5409	0.591	0.2562	0.3619	0.481	0.4514	0.5419	0.4644	0.7894
C_2	0.7008	0.6747	0.548	0.2148	0.7089	0.3649	0.2825	0.3809	0.7166	0.1217	0.7398	0.746
C_3	0.4806	0.44	0.3728	0.2086	0.4751	0.2452	0.7845	0.6533	0.6064	0.6572	0.1996	0.2488
C_4	0.4121	0.7544	0.1853	0.1	0.3052	0.3967	0.1805	0.7111	0.3478	0.5024	0.4928	0.3585
C_5	0.1509	0.3789	0.1045	0.6134	0.1797	0.3969	0.5186	0.3088	0.7938	0.4357	0.5413	0.6353
C_6	0.79	0.1483	0.3206	0.4225	0.3776	0.4713	0.3665	0.5711	0.4129	0.5537	0.6671	0.6826
C_7	0.4049	0.5688	0.7626	0.1798	0.1955	0.5398	0.1048	0.113	0.5549	0.5498	0.2003	0.6129
C_8	0.6515	0.3143	0.7373	0.717	0.2037	0.103	0.6383	0.1428	0.6055	0.318	0.2952	0.539
C_9	0.3032	0.2569	0.1398	0.1925	0.4955	0.1251	0.1369	0.4441	0.1707	0.3079	0.4742	0.6214
C_{10}	0.5141	0.1429	0.3686	0.665	0.212	0.1014	0.1912	0.5196	0.5102	0.7958	0.5949	0.4399
C_{11}	0.3544	0.4367	0.7656	0.7401	0.7846	0.36	0.1633	0.5764	0.3787	0.6032	0.4601	0.345
C_{12}	0.5558	0.7575	0.7036	0.7935	0.39	0.4607	0.1431	0.6453	0.5538	0.7631	0.2854	0.6074
C_{13}	0.3269	0.7296	0.7973	0.4498	0.3054	0.5586	0.5784	0.1679	0.3204	0.3118	0.4626	0.2408
C_{14}	0.2313	0.3992	0.7247	0.3409	0.6391	0.55	0.5596	0.4211	0.3099	0.1127	0.7782	0.4564

Table A3 (d) represents Neutrosophic matrix after applying hamming distance for the cities C_{15} to C_{26} from Table 1 in section 4.

	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	C_{26}
15	0.3269	0.2313	0.0	0.587	50.4798	0.4102	0.277	0.3913	0.7747	0.2681	0.4932	0.1883	0.1427	0.48
16	0.7296	0.3992	0.5875	0.0	0.3031	0.7394	0.2291	0.1018	0.55	0.478	0.5216	0.6383	0.7097	0.5613
17	0.7973	0.7247	0.4798	0.3031	0.0	0.6038	0.5184	0.6117	0.1639	0.5222	0.48	0.3112	0.4569	0.5877
18	0.4498	0.3409	0.4102	0.7394	0.6038	0.0	0.1905	0.3585	0.7423	0.767	0.6496	0.6868	0.7177	0.5705
19	0.3054	0.6391	0.277	0.2291	0.5184	0.1905	0.0	0.1448	0.336	0.3811	0.2179	0.1647	0.7418	0.7442
20	0.5586	0.55	0.3913	0.1018	0.6117	0.3585	0.1448	0.0	0.2731	0.4678	0.2975	0.7043	0.1269	0.3461
21	0.5784	0.5596	0.7747	0.55	0.1639	0.7423	0.336	0.2731	0.0	0.1003	0.5828	0.1995	0.1118	0.2824
22	0.1679	0.4211	0.2681	0.478	0.5222	0.767	0.3811	0.4678	0.1003	0.0	0.4584	0.6436	0.5071	0.2357
23	0.3204	0.3099	0.4932	0.5216	0.48	0.6496	0.2179	0.2975	0.5828	0.4584	0.0	0.4397	0.5777	0.4602
24	0.3118	0.1127	0.1883	0.6383	0.3112	0.6868	0.1647	0.7043	0.1995	0.6436	0.4397	0.0	0.3931	0.6435
25	0.4626	0.7782	0.1427	0.7097	0.4569	0.7177	0.7418	0.1269	0.1118	0.5071	0.5777	0.3931	0.0	0.7415
26	0.2408	0.4564	0.48	0.5613	0.5877	0.5705	0.7442	0.3461	0.2824	0.2357	0.4602	0.6435	0.7415	0.0

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